Feature Selection from Multivariate Time Series Data: A Case Study of Solar Flare Prediction

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***Abstract*—Solar physicists frequently use solar magnetic field parameters for analyzing and predicting solar events. Temporal observation of magnetic field parameters, i.e., multivariate time series (MVTS) representation facilitates finding relationships of magnetic field states to the occurrence of extreme solar events (e.g., solar flares). Feature selection of MVTS-represented solar magnetic field parameters (features) can select the most relevant parameters that give high prediction accuracy. In this paper, we propose a deep learning-based feature selection method, more specifically, an LSTM-based incremental feature selection method, as an end-to-end solution for feature selection in MVTS data. We performed LSTM-based feature selection for multivariate time series data in two steps. Firstly, each MVTS feature is evaluated individually by an LSTM-based univariate sequence classifier, and secondly, the top-performing features are combined to produce input for a downstream LSTM-based multivariate sequence classifier. We compared the proposed MVTS feature selection method with three other baseline feature selection methods on an MVTS-based solar flare prediction dataset and demonstrated that our method selects more discriminatory features compared to other methods.**

***Index Terms*—Feature selection; LSTM; Deep Learning; Multivariate time series, Solar Physics, Solar Magnetic Field Parameters**

I. Introduction

Photospheric magnetic field parameter values such as helicity, flux, Lorentz force, currents, and shear angles are used to characterize solar events such as flares, coronal mass ejection (CME), and eruption of solar energetic particles (SEP) [1], [2]. Among these events, solar flares are caused by a sudden burst of magnetic flux from the corona. The X-ray radiation of extreme solar flares can have devastating effects on life and infrastructure on earth and space such as GPS and radio communication disruption, radiation exposure-based health risks to the astronauts, and damage to electronic devices. The infrastructure damage after extreme solar events can cost trillions of dollars [3]. Accurate prediction of solar flares given a predefined time window has become an important challenge in the heliophysics community. Since the theoretical relationship between magnetic field influx and the occurrence of flaring activities in the solar active regions (AR) is not yet established, space weather researchers depend on the data science-based approaches for predicting solar events.

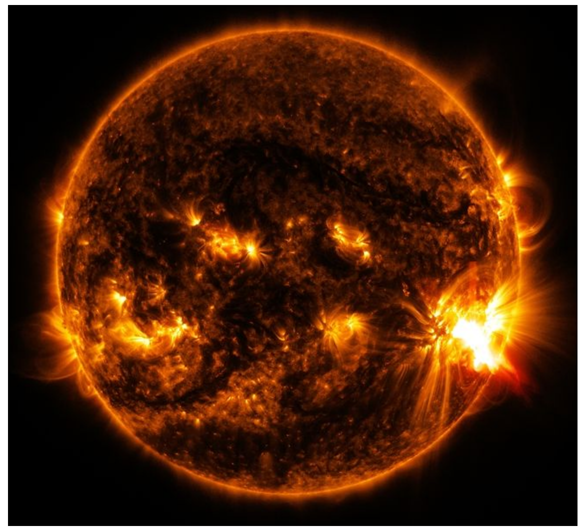


Fig. 1: X2.0-class solar flare in the lower right side of the Sun on Oct. 27, 2014, 10:47 a.m. EDT. Image Credit: NASA/SDO

The primary data source used in these efforts is the images captured by the Helioseismic Magnetic Imager (HMI) located in the Solar Dynamics Observatory (SDO). HMI images (captured in near-continuous time) contain spatiotemporal magnetic field data of the solar active regions. For performing temporal window-based flare prediction of an AR instance, the magnetic field data of that region is mapped into a multivariate time series (MVTS) instance [1]. MVTS instances, collected with a uniform sampling rate throughout a preset *observation period*, are labeled with multiple flare classes (e.g., flare-quiet, A, B, C, M, and X), and machine learning-based classifiers are trained with labeled MVTS instances to predict the occurrences of the events within a preset *prediction window*. Fig. 1 shows an X-class flare recorded by NASA's Solar Dynamics Observatory (SDO).

Although multiple research efforts [4]–[7] addressed MVTS-based solar event prediction, in this work, we propose a two-step deep learning framework for the feature selection from MVTS-represented solar flare data. In the first step, we apply a univariate sequence learning using individual parameters to get their validation accuracy (importance score). An importance score for each parameter is calculated using Long Short Term Memory(LSTM) classifier. In the second step, we sort the parameter's importance scores from the first step. Then we utilize them to find the cumulative validation accuracy of the top parameters list to get the optimal parameters set (features) to be used when we test the data. The key contributions of this study are:

- We propose a two-step deep learning LSTM-based framework for the MVTS feature selection.
- We can train our framework with various downstream classifiers like LSTM, SVM, etc. to perform MVTS classification
- The experimental results of our model conducted a validation accuracy of 69% on the solar flare MVTS dataset when using SVM as a downstream classifier. Which outperformed the traditional feature selection models(the baselines) by more than 10%.

II. Related work

In space weather research, solar events are studied for understanding their influences on the nature of geomagnetic fields and how they can interact with the electromagnetic systems of the Earth. Extreme solar events, e.g., major solar flares can affect the radiation environment outside the Earth's magnetosphere which is explored by many space missions. These events can cause an extreme radiation exposure-based threat to astronauts on space missions [8], [9]. Recent research efforts on solar flare prediction mostly are based on data science (e.g., machine learning). Data-driven extreme solar event prediction models stem from linear and nonlinear statistics. Datasets used in the statistical models were collected from line-of-sight magnetogram and vector magnetogram data. Line-of-sight magnetogram contains only the line-of-sight component of the magnetic field, while vector magnetogram contains the full disk magnetic field data [10]. NASA launched Solar Dynamics Observatory (SDO) in 2010. Since then, SDO's instrument Helioseismic and Magnetic Imager (HMI) has been mapping the full-disk vector magnetic field every 12 minutes [2]. Most of the recent prediction models use the near-continuous stream of vector magnetogram data found from SDO [11]. Magnetic field parameters (e.g., helicity, flux, etc) were developed to find the relationships between the phosphoric magnetic field states and the following solar activities.

Feature selection plays an important role in dataset preprocessing and performance boosting of ML models, especially in the presence of high-dimensional data. For solar flare data, each example of a flaring or non-flaring AR is characterized by a feature vector of magnetic field parameters. High dimensionality in this vector-based dataset may result in low performances for the classifiers. Dimensionality reduction by selecting the most discriminatory features can increase the classification performance by reducing the overfitting tendency [2]. Han et. al [12] proposed a filter-based method for feature selection from multivariate time series with the trace-based class separability criterion. The model is called class separability feature selection (CSFS), and uses the Mutual Information (MI) matrix of the multivariate time series (MVTS) items as the features for classification and ranks the variables according to the class separability. Ircio et. al [13] proposed a feature subset selection method in MVTS classification using mutual information. Gu et. al [14] proposed a network pruning feature selection approach (NFS), an end-to-end feature selection framework for MVTS data. This is a neural network model based on decomposed convolution, in which a temporal convolutional neural network (CNN) processes each feature stream within MVTS input independently, and an aggregating CNN combines all the streams to extract channel-wise information. Deep learning sequence models such as recurrent neural networks (RNN) use sequential data or time series data. They have been used for temporal or ordinal problems such as machine translation [15]and text summarization [16]. They are indicated by their memory as they take information from prior inputs to influence the current input and output. The output of recurrent neural networks depends on the prior features within the sequence. Long short-term memory (LSTM) is a popular RNN architecture that addresses the problem of long-term dependencies [17]. They provide a powerful solution for various sequence learning tasks. Since the multivariate time series are high-dimensional sequence data, in our study, we propose two-step deep learning framework for the MVTS feature selection. In the first step, we apply a univariate sequence learning method using LSTM for feature selection. In the second step, we apply LSTM-based MVTS feature selection.

III. Methodology

A. Notations

The solar event instance i is represented by an MVTS instance $mvts_i$. The MVTS instance $mvts_i \in \mathbb{R}^{T\times N}$ is a collection of individual time series of N magnetic field parameters, where each time series contains periodic observation values of the corresponding parameter for an observation period T. In the MVTS instance $mvts_i = \{v_{t_1}, v_{t_2}, ., ., ., v_{t_T}\}$, where $v_{t_i} \in \mathbb{R}^N$ represents a timestamp vector.

B. Data Preprocessing

Suppose that M number of MVTS instances each with N parameters and T time points are represented as $mvts_i \in \mathbb{R}^{T\times N}$ where $1 \leq i \leq M$. Each column P_j of $mvts_i$ is an univariate time series $P_j \in \mathbb{R}^T$, where $1 \leq j \leq N$. we perform z-normalization for each column P_j as the following.

$$X_k{}^j = \frac{X_k{}^j - \mu^j}{\sigma^j} \tag{1}$$

Here, $X_k{}^j$ is the is the k-th value of the time series P_j where $1 \leq k \leq T$, $\mu^j$is the the mean of time series P_j and σ^j is the standard deviation of the time series P_j .

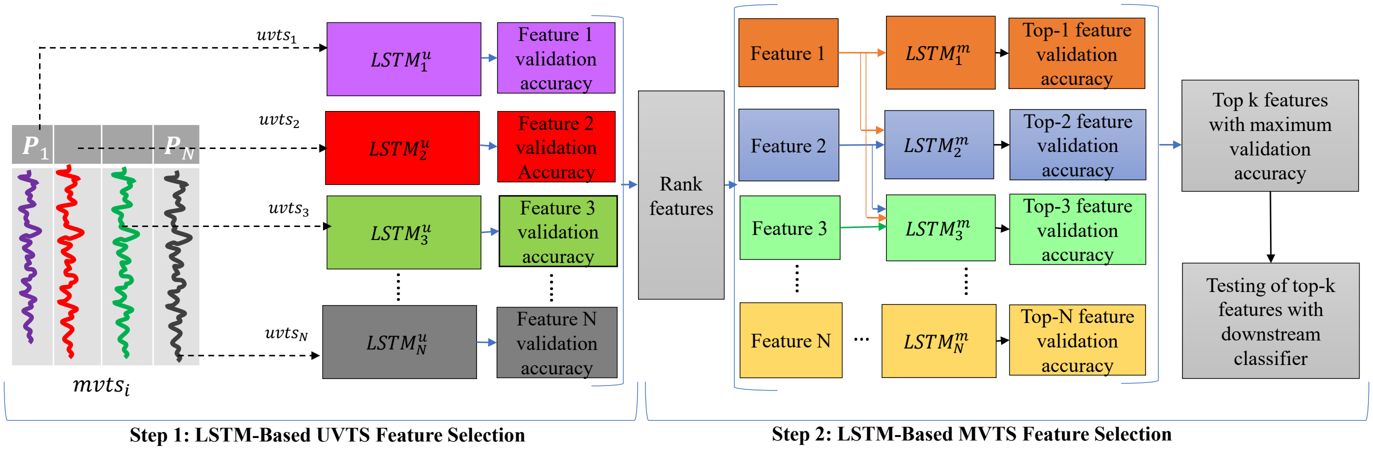


Fig. 2: Deep Learning MVTS Feature Selection Framework

C. LSTM-based MVTS Feature Selection Framework

Algorithm 1 LSTM-Based UVTS Feature Selection

Input: Training set $X\_train \in \mathbb{R}^{n_{train} \times N \times T}$, training labels $Y\_train \in \mathbb{R}^{n_{train} \times C}$, validation set $X\_val \in \mathbb{R}^{n_{val} \times N \times T}$, validation labels $Y\_val \in \mathbb{R}^{n_{val} \times C}$, and number of training epochs n_{epochs}. Here, C is the number of classes, n_{train} and n_{val} is the number of examples in the train and validation sets, and the labels are in one-hot representation.

Output: Validation accuracy of each individual parameter.

for parameters $j = 1$ to N **do**
  Initialize weight and bias of $LSTM_j^u$
  for number of training epochs $e = 1$ to n_{epochs} **do**
    for MVTS instance $i = 1$ to n_{train} **do**
      $train\_mvts = X\_train[i,:,:]$
      $train\_uvts = train\_mvts[j,:]$
      $target = Y\_train[i]$
      $scores = LSTM_j^u(train\_uvts)$
      $loss = negative\_log\_likelihood(scores, target)$
      $loss.backward()$
    end for
    $numCorrect\_val = 0$
    for MVTS instance $i = 1$ to n_{val} **do**
      $val\_mvts = X\_val[i,:,:]$
      $val\_uvts = val\_mvts[j,:]$
      $val\_label = Y\_val[i]$
      $val\_class\_scores = LSTM_j^u(val\_uvts)$
      $val\_prediction = argmax(val\_class\_scores)$
      if $(val\_prediction == val\_label)$ **then**
        $numCorrect\_val = numCorrect\_val + 1$
      end if
      $val\_accuracy = (numCorrect\_val / n_{val})$
      $univariate\_importance[j] = val\_accuracy$
    end for
  end for
end for
return $univariate\_importance$

Algorithm 2 LSTM-Based MVTS Feature Selection

Input: $univariate\_importance \in \mathbb{R}^N$, X_{train}, Y_{train}, X_{val}, Y_{val}, n_{epochs}

Output: Feature set producing best validation accuracy.

Sort the parameters in descending order according to $univariate\_importance$
for sorted parameters $j = 1$ to N **do**
  $topK = list(1:j)$
  Initialize weight and bias of $LSTM_j^m$
  for number of training epochs $e = 1$ to n_{epochs} **do**
    for MVTS instance $i = 1$ to n_{train} **do**
      $train\_mvts = X\_train[i,:,:]$
      $train\_mvts\_topK = train\_mvts[topK,:]$
      $target = Y\_train[i]$
      $scores = LSTM_j^m(train\_mvts\_topK)$
      $loss = negative\_log\_likelihood(scores, target)$
      $loss.backward()$
    end for
    for MVTS instance $i = 1$ to n_{val} **do**
      $val\_mvts = X\_val[i,:,:]$
      $val\_mvts\_topK = val\_mvts[topK,:]$
      $val\_label = Y\_val[i]$
      $val\_class\_scores = LSTM_j^m(val\_mvts\_topK)$
      $val\_prediction = argmax(val\_class\_scores)$
      if $(val\_prediction == val\_label)$ **then**
        $numCorrect\_val = numCorrect\_val + 1$
      end if
      $val\_accuracy = (numCorrect\_val / nVal)$
      $multivariate\_importance[j] = val\_accuracy$
      $topK\_features[j] = topK$
    end for
  end for
end for
return $topK\_features[argmax(multivariate\_importance)]$

First, we divide the dataset into training, validation, and test sets. Then we apply a two-step deep learning-based feature selection approach (Fig. 2). The first step uses sequence classification from the univariate time series (UVTS) of the individual parameters. After training N univariate LSTM classifiers ($LSTM^u$) with each parameter individually, we calculate the validation accuracy of each parameter to get an importance score for each parameter. In the second step, we rank the parameters according to their individual validation accuracy (importance score) from highest to lowest. Then, we incrementally select top-k performing parameters with high validation accuracy and train LSTM-based multivariate sequence classifiers ($LSTM^m$) with multiple selected parameters. The parameter set that produced maximum validation accuracy is selected for testing on the test set using a downstream classifier (e.g., LSTM, SVM, etc). Algorithm 1 and 2 explain our two-step MVTS feature selection method from MVTS data.

TABLE I: Active Region Magnetic Field Parameter Names and Description

Parameter	Description
TOTPOT	Total photospheric magnetic free energy density
MEANJZD	Mean vertical current density
MEANGBZ	Mean gradient of vertical field
MEANGBH	Mean gradient of horizontal field
AREA_ACR	Area of strong field pixels in the active region
USFLUX	Total unsigned flux
SHRGT45	Fraction of Area with Shear $> 45°$
MEANPOT	Mean photospheric magnetic free energy
MEANGBT	Mean gradient of total field
MEANSHER	Mean shear angle
R_VALUE	Sum of flux near polarity inversion line
ESPX	Sum of x-component of normalized Lorentz force
TOTFZ	Sum of z-component of Lorentz force
MEANGAM	Mean angle of field from radial
EPSZ	Sum of z-component of normalized Lorentz force
MEANJZH	Mean current helicity (B_z contribution)
TOTUSJZ	Total unsigned vertical current
MEANALP	Mean characteristic twist parameter,α
TOTFX	Sum of x-component of Lorentz force
TOTFY	Sum of y-component of Lorentz force
ESPY	Sum of y-component of normalized Lorentz force
ABSNJZH	Absolute value of the net current helicity
SAVNCPP	Sum of the modulus of the net current per polarity
TOTBSQ	Total magnitude of Lorentz force
TOTUSJH	Total unsigned current helicity

IV. Experiments

In this section, we demonstrate our experimental methods and results. We compared our LSTM-based feature selection model with three baseline methods(Fisher Score , Mutual Information, and minimal Redundancy Maximal Relevance) for selecting the best discriminatory features on a MVTS-based flare prediction dataset. First, we extract important features from the training and validation datasets using each method, and then we used the selected features for classifying the test instances using a downstream classifier. We reported the best-selected features found by each method and the corresponding test accuracy of the downstream classifier. We applied random sampling for train/validation/test splitting, where we used the stratified splitting method (70 % for training, 10 % for validation, and 20 % for test) with six different random seeds, and reported the mean test and validation accuracy along with standard deviation. Train, validation, and test datasets are z-normalized since magnetic field parameter values appear on different scales. For LSTM feature selection and LSTM downstream classifier, we use the number of hidden layer units as 128, the number of training epochs as 20, and the learning rate in stochastic gradient descent as 0.01. For SVM downstream classifier we use the regularization parameter C as 1.0, the kernel as radial basis function(RBF), and gamma as scale. The source code of our model and the experimental dataset are available on our GitHub repository [1].

A. Dataset Description

As the benchmark dataset of our experiments, we used the MVTS-based solar flare prediction dataset published by Angryk et. al [1]. Each MVTS instance in the dataset is made up of 25 time series of active region magnetic field parameters (a full list can be found in Table 1). The time series instances are recorded at 12 minutes intervals for a total duration of 12 hours (60-time steps). The dataset has the number of observation points T = 60, and the number of parameters N = 25. Our experimental dataset consists of 1,540 MVTS instances that are evenly distributed across four flare classes (X, M, BC, and Q), where Q represents flare-quiet events, and BC represents a mix of B and C class events.

B. Baselines methods

For baselines, we used Fisher Score(FS), Mutual Information(MI), and minimal Redundancy Maximal Relevance(mRMR) feature selection algorithms.

Fisher score (FS) applies importance scores on each feature independently in accordance with their class labels.

Mutual information (MI) is a measure of the mutual dependence between the two variables, and quantifies the entropy obtained about one random variable (features) by observing the other random variable (labels).

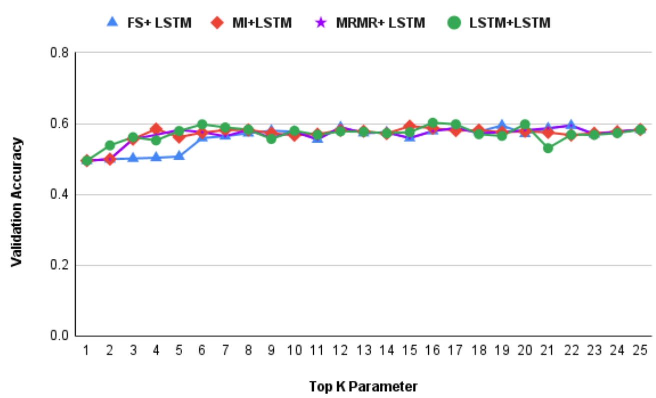
Minimal Redundancy Maximal Relevance - (mRMR) is a multivariate feature scoring method, where at each iteration it selects the features that have the maximum relevance with the target variable and minimum redundancy with the features that have been selected at previous iterations.

For applying the baseline methods on the MVTS dataset, we used mean reduction, where for each MVTS instance $mvts_i$ we calculate the mean for each column(feature or parameter) to get a vector-based dataset($mvts_i$ to $uvts_i$). Then we performed feature scoring, where we found Fisher, MI, and mRMR scores for each parameter. Finally, we applied incremental feature selection based on those scores on the validation dataset to find the best candidate parameters for testing them with a downstream classifier. We used LSTM and SVM as downstream classifiers.

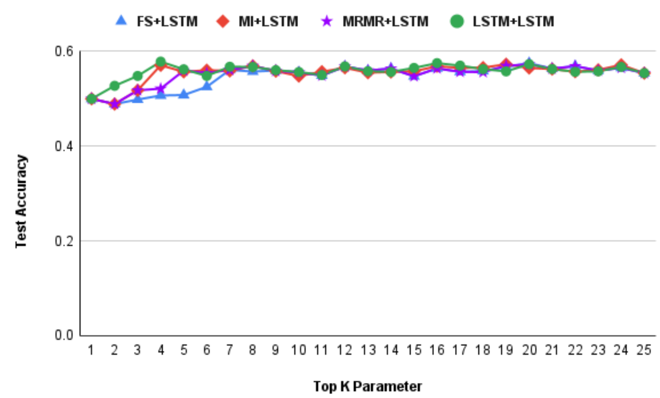
[1] https://github.com/Kalshammari/MVTSFeatureSelection

TABLE II: Top Parameters of LSTM, Fisher Score, MI and mRMR, and Classifiers Test Accuracy

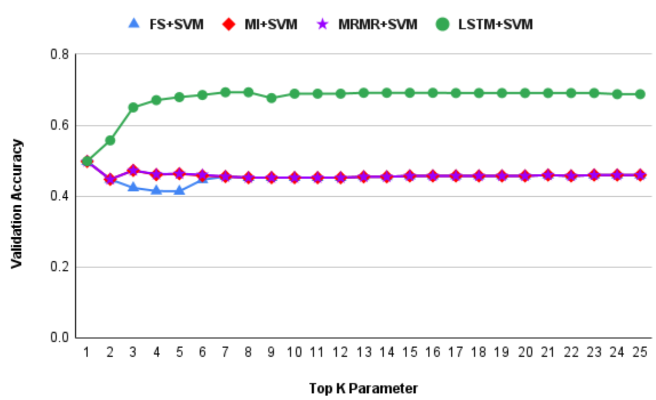
	LSTM	Fisher Score	MI	mRMR
Top parameters names	TOTPOT MEANJZD MEANGBZ MEANGBH AREA_ACR USFLUX SHRGT45	TOTPOT AREA_ACR TOTFZ MEANGAM MEANSHER MEANGBH MEANJZD	TOTPO AREA_ACR MEANGBH MEANJZD USFLUX TOTFZ MEANSHER	TOTPO AREA_ACR MEANGBH TOTFZ MEANJZD MEANGAM MEANSHER
Number of selected parameters	**7**	7	7	7
LSTM Classifier Highest Validation Accuracy	**0.597**	0.564	0.581	0.564
LSTM Classifier Highest Test Accuracy	**0.578**	0.560	0.558	0.560
SVM Classifier Highest Validation Accuracy	**0.692**	0.455	0.455	0.455
SVM Classifier Highest Test Accuracy	**0.677**	0.446	0.455	0.456



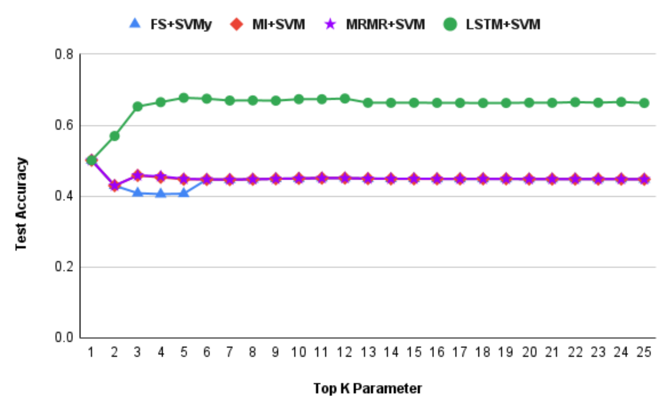
(a) LSTM Classifier Validation Accuracy Results



(b) LSTM Classifier Test Accuracy Results.



(c) SVM Classifier Validation Accuracy Results.



(d) SVM Classifier Test Accuracy Results.

Fig. 3: Validation and test accuracy of downstream LSTM and SVM classifiers after applying incremental feature selection using all discussed methods

C. Comparison of LSTM-based MVTS Feature Selection with other Baselines

We apply LSTM-based MVTS feature selection on the solar flare MVTS dataset. Then, we apply the baseline methods(FS, MI, and mRMR) on the same dataset. Our experimental results showed that the LSTM-based MVTS feature selection method outperformed the baseline approaches by more than 10%. We found out that our method gives the highest validation accuracy with the top seven parameters(TOTPOT, MEANJZD, MEANGBZ, MEANGBH, AREA_ACR, USFLUX, and SHRGT45) with SVM. Table II shows the top parameters of LSTM, Fisher Score, MI, and mRMR, and their LSTM and SVM classifiers validation and test accuracy. Figures 3a and 3b show the validation and test accuracy results using the LSTM classifier with LSTM-based MVTS feature selection, FS, MI, and mRMR for feature selection. Figure 3a shows that the LSTM classifier achieves its best validation accuracy(0.597) with the top six parameters when using LSTM-based MVTS feature selection. Figure 3b shows that the LSTM classifier achieves its best test accuracy(0.578) with the top four parameters when using LSTM-based MVTS feature selection. Figures 3c and 3d show the validation and test accuracy results using the SVM classifier with LSTM-based MVTS feature selection, FS, MI, and mRMR for feature selection. Figure 3c shows that the SVM classifier achieves its best validation accuracy(0.692) with the top seven parameters when using LSTM-based MVTS feature selection. Figure 3d shows that the SVM classifier achieves its best test accuracy(0.677) with the top five parameters when using LSTM-based MVTS feature selection.

V. Conclusion

In this work, we presented a two-step deep learning-based framework for feature selection from multivariate time series data, and applied the method on a benchmark solar flare prediction dataset for finding discriminatory magnetic field parameters. In the first step, feature importance score of each individual parameter is approximated by an application of LSTM-based univariate sequence classifier. Finally, the best feature set that can jointly discriminate examples are extracted by applying LSTM-based multivariate sequence classifier. The discrimination ability of the selected feature set is assessed by testing with a downstream classifier. On the solar flare prediction dataset, our two-step LSTM-based feature selection model followed by a downstream SVM classifier outperformed the baseline feature selection approaches by more than 10%.

In the future, we plan to work on graph-based feature selection from MVTS data. MVTS data represented by graphs, aka networks, can encode higher order relationships between the variables [18], [19]. We are interested in the application of graph neural networks on MVTS-graphs to extract graph-level discriminatory feature set represented by sub-graphs, paths, cycles, and so on. We also look forward to applying our feature selection method on other MVTS datasets, such as brain region time course data extracted by functional magnetic resonance imaging (fMRI) [20].

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